

Annual Progress Report

Titled:

A Methodology to Create a Unified Trade-Off Environment for Advanced Aerospace Vehicle

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Background

Motivation

The Joint Multi-Role Rotorcraft (JMR) program is intended to demonstrate technology for a family of rotorcraft that could eventually replace its entire fleet of helicopters — attack, reconnaissance, utility and cargo — as well as similar platforms operated by the U.S. Navy, Marine Corps and Air Force. Currently, the Army uses a heavily upgraded fleet of helicopters. The upgrades offer marginal improvements in performance over their non-upgraded counterparts. The focus with JMR is on replacing the “medium” fleets of AH-64 Apaches and UH-60 Black Hawks, but the demonstrator configurations must be scalable downward to replace OH-58D Kiowa Warrior armed scouts and potentially upward to replace heavy-lift CH-47 Chinooks, as shown in Figure 1.

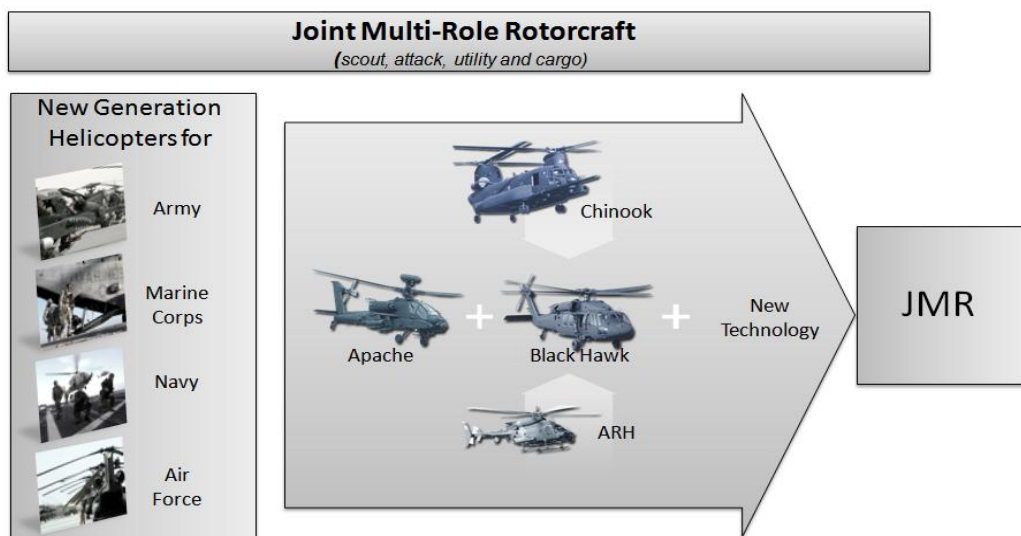


Figure 1: Joint Multi-Role Rotorcraft Program Architecture

Advanced and compound helicopters as well as tiltrotors are under the consideration for a potential JMR platform with the technology exploration to increase speed, range, payload, survivability and reliability. The development and evaluation of the JMR Demonstrator vehicle(s) will offer tremendous payoff for the entire rotary wing community. It will allow for

the pursuit of significant improvements in performance, survivability, commonality, and sustainability. It will provide essential insights as to the warfighter capabilities that are both achievable and affordable for the next generation fleet. Investigations are already underway by AFDD and the Design IPT using NASA Design and Analysis of Rotorcraft (NDARC)ⁱ software, which has been under development since 2007. NDARC is the primary rotorcraft sizing and synthesis code used to compare JMR configurations and technologies. The JMR mission profile is designed to meet the future vertical lift needs of the armed forces. The high speed and high altitude requirements drive higher weight and cost given today's technologies. Thus JMR will require "game changing" technologies. The Aerospace Systems Design Lab (ASDL) at Georgia Tech has been involved with a number of projects to develop and analyze tools with the capabilities to rapidly and dynamically evaluate and compare scenarios and enable real-time strategy exploration and trade-offs. The motivation for this ASDL task is that our experience in Quantitative Technology Assessment (QTA) can be utilized in support of trade studies currently being undertaken by AFDD for the JMR.ⁱⁱ

The Problem Definition

The Joint Multi-Role Rotorcraft Technology Demonstrator (JMR TD) is intended to demonstrate technologies for a family of rotorcraft that could eventually replace an entire fleet of helicopters. During the JMR TD effort, multiple rotorcraft configurations are being analyzed for their performance and mission effectiveness across a joint set of roles and operations. One anticipated outcome of the JMR TD effort is the identification of capability gaps and the impact that technologies can have on closing the gaps. In order to realize this outcome, there is a need for quantitative assessment of technology impact on rotorcraft capabilities.

The problem for the Design IPT team deals with arriving at a reasonably good guess at what a particular configuration will look like in terms of weight, performance, cost, and other system metrics given a set of requirements for the platform. Predicting the size, weight, and performance of a configuration is not that difficult using a tool such as the NASA Design and Analysis of Rotorcraft (NDARC) software, which was specifically created to aid in rotorcraft

conceptual design and technology impact analysis. The difficulty and challenge is being able to model current and future technologies in a way that makes sense, is believable, and also traceable. The real challenge is not the process itself. The real challenge is in answering the following questions:

1. What are the technologies that the Design IPT should be considering for the various JMR configurations?
2. What parameters in my tool are impacted – either positively or negatively – by each technology?
3. What is the range that I might expect the impact to be in actual numbers? (i.e. 0.5 – 1.2)
4. Which technologies are compatible? Which are incompatible?
5. What are the impacts of the technologies on enterprise goals?
6. What are the most important/significant trades in the design?

By answering the questions above, NDARC can be used to quantify the impact of the technologies listed. Figure 2 is summary of Quantitative Technology Assessment (QTA) process using the NDARC. Each technology will be transferred to technology factors in the NDARC input set and the effects are analyzed through the NDARC analysis.

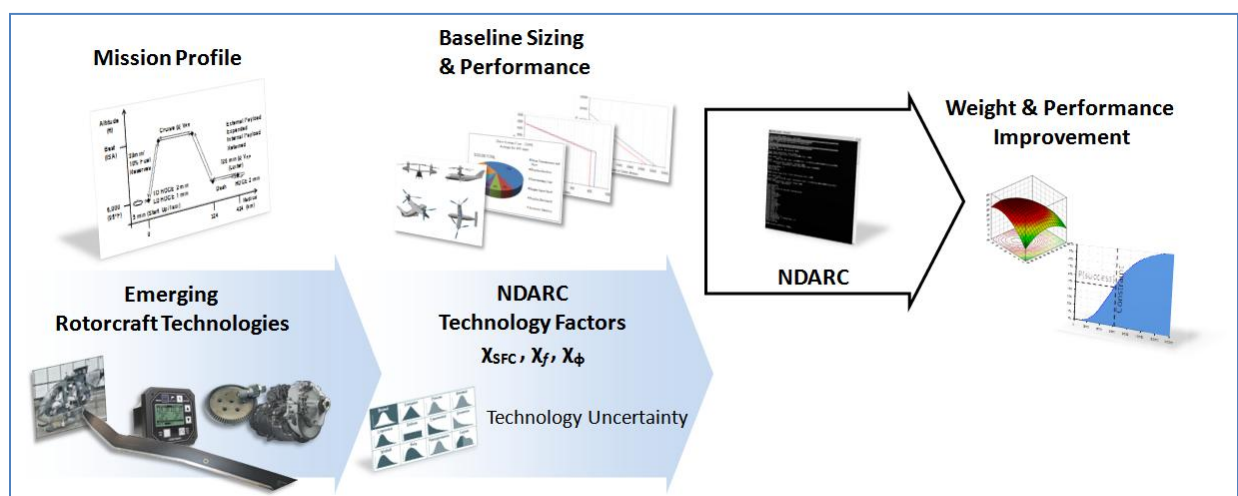


Figure 2: JMR Quantitative Technology Assessment Overview

Previous Research Tasks

NDARC Familiarization and Implementation

One of the first tasks in beginning to address JMR vehicles and their technologies was for the team to familiarize itself with the modeling capabilities of NDARC. To do so, NDARC was used to size a vehicle to a public set of mission requirements that reflected the JMR missions. These requirements were found in the 2011 AHS student design competition. Sizing a vehicle to those requirements helped familiarize the research with NDARC. During this task, technology variables were identified, which are outlined in the next section.

Identification of Technology Variables inside NDARC

NDARC has built-in technology factors to reflect influence of advanced technology. These technology factors are used for parametric calculation of component weight, profile power, and cost as follows:

$$W = \chi W_{\text{model}} + dW$$

where, W = weight of individual elements in a group, and dW = weight increment.

$$c_{\text{dmean}} = \chi S(c_{\text{dbasic}} + c_{\text{dstall}} + c_{\text{dcomp}})$$

where, c_{dmean} = mean drag coefficient, χ =technology factor, c_{dbasic} = basic drag coefficient, c_{dstall} =stall drag coefficient, and c_{dcomp} =compressibility drag coefficient.

$$C_{\text{AC}} = F_i(\chi_{\text{AF}}c_{\text{AF}} + C_{\text{MEP}} + C_{\text{FCE}})$$

$$C_{\text{maint}} = F_i\chi_{\text{maint}}C_{\text{maint}}$$

where, C_{AC} =fly away cost, F_i =inflation factor, χ =technology factor, C_{MEP} = mission equipment package (MEP) cost, C_{FCE} =flight control electronics (FCE) cost, c_{AF} = base aircraft cost, and C_{maint} =maintenance cost per flight hour.

The engine model accounts for advanced technology by specifying the specific power, specific fuel consumption, and specification turbine speed: $\text{SP0C} = \text{SPtech}$, $\text{sfc0C} = \text{sfctech}$, $\text{Nspec} =$

Ntech. In addition to the built-in technology factors, there are other design variables that can directly reflect advanced technology, e.g. drag parameters and inflow parameters.

Literature Survey on Technology Factors

A literature survey^{iii,iv,v,vi,vii,viii,ix,x} was performed to get an initial idea on technology factors in NDARC. The purpose of the literature survey was to establish a frame of reference for potential improvement in performance of various rotorcraft subsystems as well as a framework of traceability for documenting literature on technologies identified for evaluation in the NDARC sizing code. It is important to note that a particular technology may provide improvement in a certain aspect of weight or fuel burn while resulting in a penalty of additional weight elsewhere, and thus the overall effect of potential technologies can only be feasibly assessed with collaboration between this evaluation effort and the respective disciplines corresponding to each technology.

ModelCenter Environment

ModelCenter is an MDO tool which allows users to easily construct complex environment with many tools linked together. Its primary function is to call and run the specified programs. Because NDARC reads in input files and generates output files, it was able to be plugged into the ModelCenter environment via a customized file wrapper. The screen shot of the ModelCenter environment that called-in the NDARC file wrapper is shown in Figure 3. Figure 4 shows an example of how an output file is linked to the ModelCenter graphical environment.

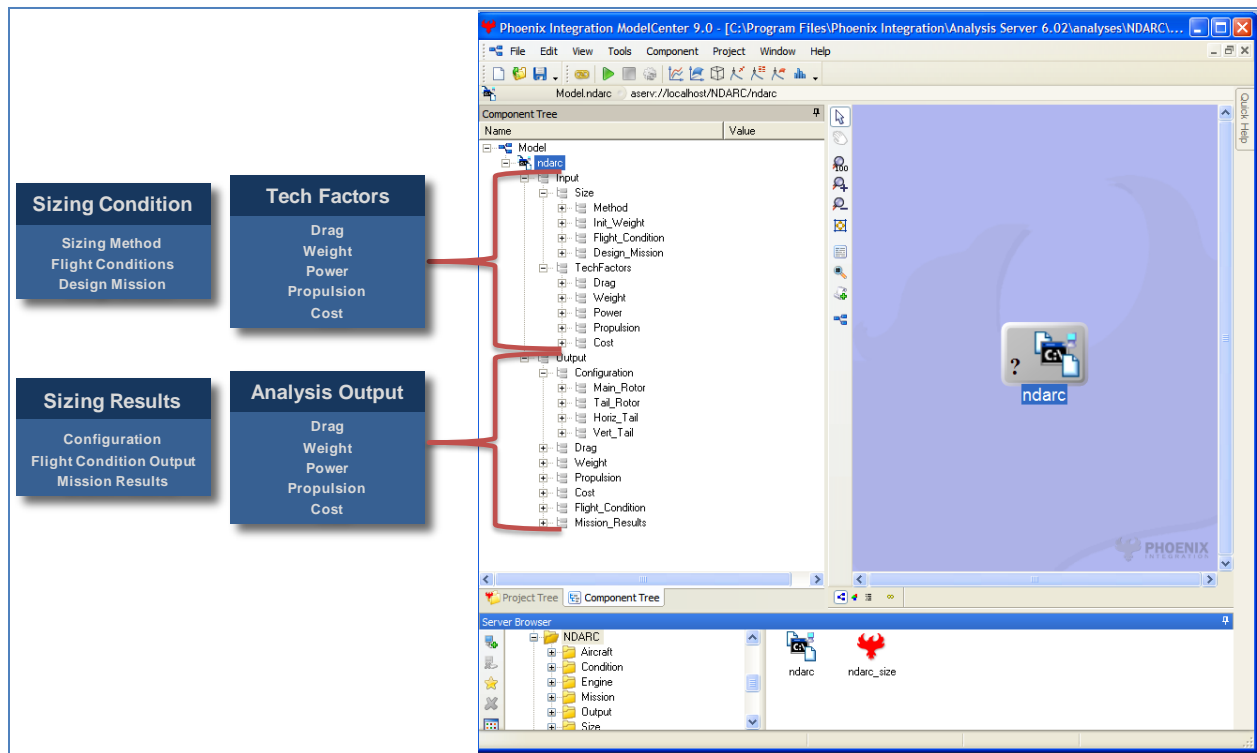


Figure 3: NDARC in ModelCenter

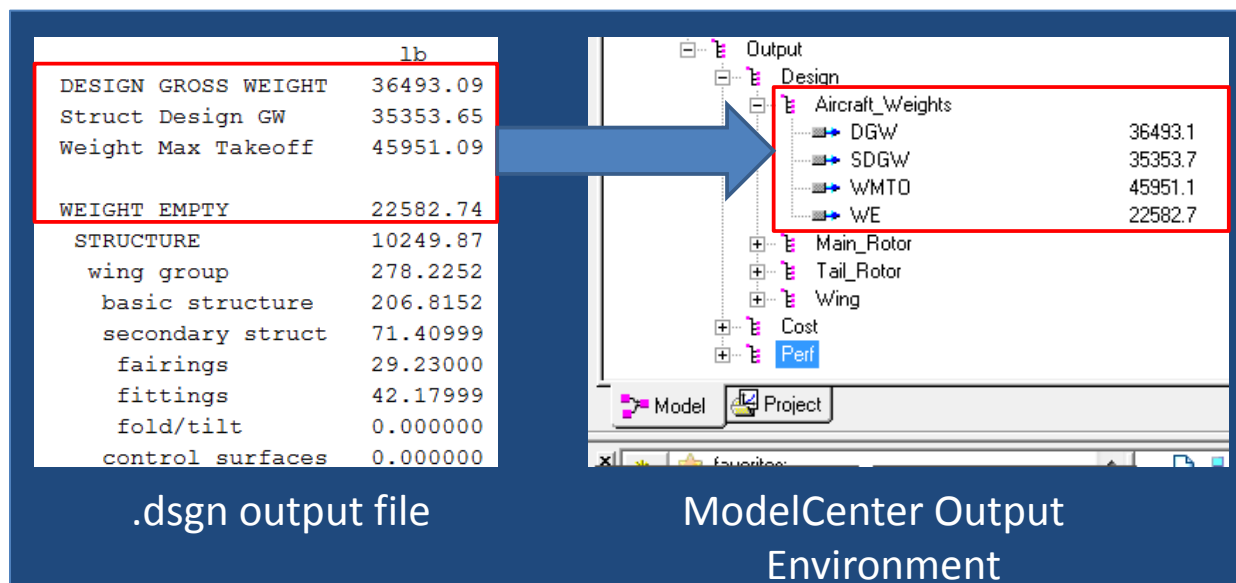


Figure 4: ModelCenter Linkage to NDARC Output Files

In order to build an environment capable of answering complex questions about technologies, missions, and requirements, the sizing tool and its results must be studied over a wide range of input values. ModelCenter provides features to do this, through the creation and application of Design of Experiments (DoEs), parametric studies, and carpet plots for analysis. The DoE tool is the most valuable, because it allows the purposeful changing of input values in order to maximize the value of output information while simultaneously attempting to minimize the cost, in terms of time and effort, of gathering that information. It is that capability that forms the basis of surrogate modeling; a powerful tool for rapid analysis and decision making. Later sections of this document outline the surrogate modeling effort, and its value.

JMR Technology Sensitivity Study

Of principal interest to the research is the impact of technology on the attributes and performance of rotorcraft, particularly the weight of the vehicle. This section summarizes a set of helicopter sizing studies that quantified the effect of new technology insertion at the subsystem level on design parameters – most importantly aircraft empty weight – at the group and overall system level of the vehicle’s weight statement. The design parameters were analyzed for their importance to the vehicle design, and then selected for inclusion as technology factors for later research.

That research used the technology impact assessment flexibility of NDARC to explore a trade space of possible technologies which are represented by weight savings factors, or “tech factors” in the NDARC aircraft file, applied to each component of a sized aircraft’s weight statement. A methodology was developed to observe and quantify the global effect of each tech factor on the total empty weight of the vehicle. A baseline sizing model for a Medium Utility/Attack helicopter was integrated into ModelCenter. The code wrapped into the ModelCenter environment was then used to perform a set of preliminary DOE’s on weight. The DOE’s were designed using the statistical analysis software JMP, and the output files parsed by ModelCenter were fed back to JMP for analysis to determine the most impactful tech factors, as shown in Figure 5.

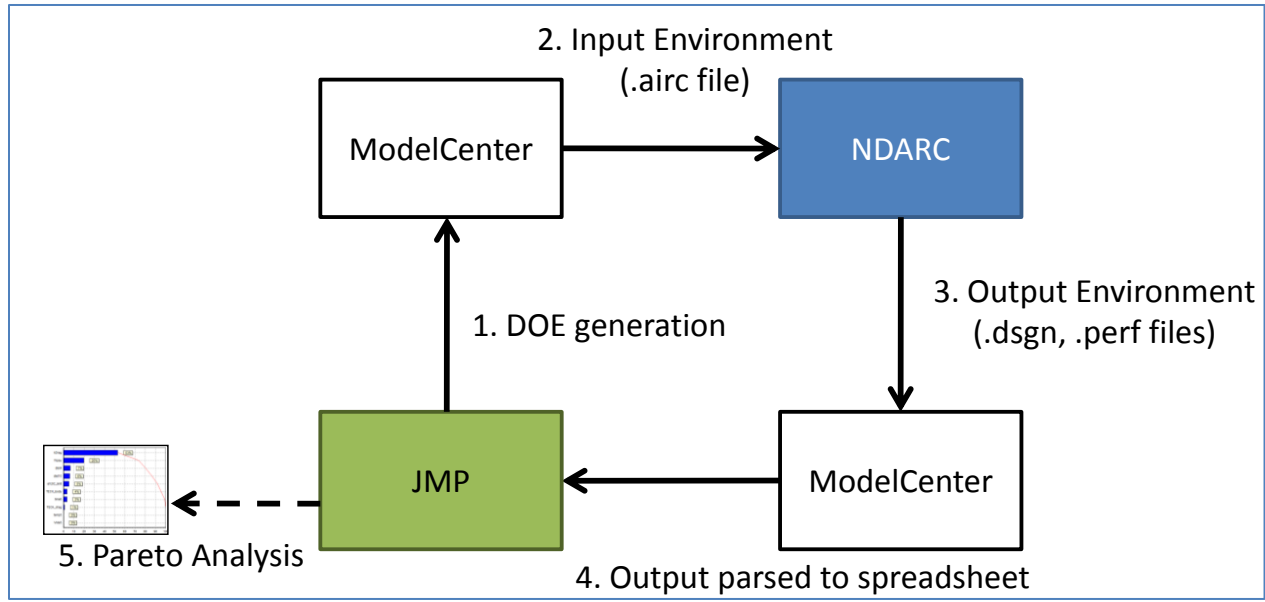


Figure 5: JMR Tech Sensitivity Analysis Data Flow

NDARC not only includes tech factors to account for weight savings, but also tech factors to model improvements in rotorcraft propulsion and aerodynamics. This presented a very large trade space of possible technology benefits to consider in the initial test runs of the ModelCenter environment. Given that it is also possible for a technology to be modeled through multiple tech factors, such as weight, power, and drag, the number of tech factors that need to be assessed to cover a wide range of technologies is very large. Thus the initial phase of the sensitivity assessment was designed to produce plots of technology impact at as low a cost as possible, to enable more precise studies later on when the important technology factors had been discovered.

The output of the technology sensitivity assessment is a ranking of which technology factors in NDARC had the largest impact, which are graphed in Pareto plots. Figure 6 displays the results of the preliminary DOE, plotting the relative influence of the tech factors on aircraft empty weight.

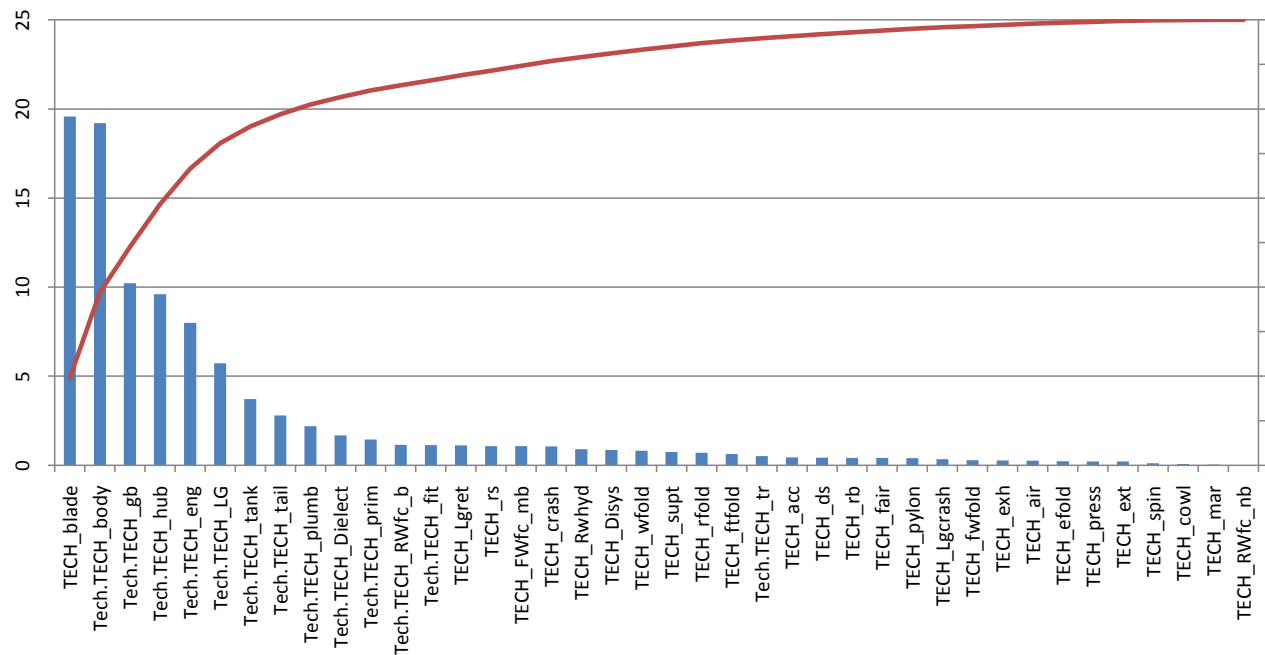


Figure 6: Preliminary DOE Empty Weight Pareto Results

Figure 7 shows the 8 most influential variables in the preliminary DOE. These variables account for 82% of the total influence on empty weight. They were retained for use in the more detailed DOE's that followed, which needed to use more input points throughout the trade space of tech factors to create more accurate response surfaces, while eliminating the variables shown to be of lesser significance.

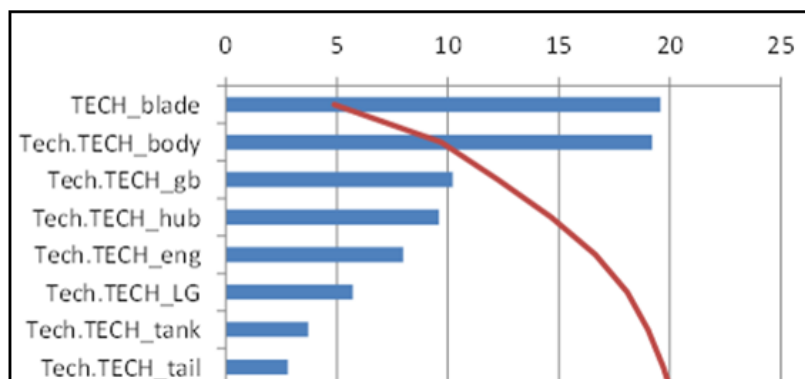


Figure 7: Preliminary DOE Highest Influence Tech Factors on Empty Weight

JMR Capability Assessment and Tradeoff Environment

This section briefly reviews the process and results of building an environment capable of performing assessments of JMR technologies, vehicles, and missions. Building the Capability Assessment and Tradeoff Environment (CATE) required two parallel efforts: analyzing and building the representation of the concept analysis tool, NDARC; and creating the environment itself in such a way to provide an intuitive and meaningful interface to the results from NDARC. The first effort was required in order to enable rapid evaluation of concepts and trade-offs. The second effort not only implemented the rapid analysis capabilities through surrogate modeling and a graphical front-end, but has additional features to enable further study of selected concepts. The goal of both efforts was to synthesize and display information and features that enables stakeholders to ask “what-if?” questions and gain fast, meaningful answers.

The first fork of the process, focused on the creation of surrogate models and other data to support the CATE, is shown in Figure 8. It began with a variable screening study, which was done to both ease the creation of surrogate models, as well as to emphasize the most impactful and relevant vehicle properties. A selection of variables was made from that study for inclusion in the environment. The surrogate modeling began with variable range selection and the creation of a Design of Experiments (DoE). The DOE was then used to efficiently sample the design space to create surrogate models. The surrogate models were built using standard techniques and then implemented in the CATE.

The second fork of the process, which is the creation of the user interface of the CATE, was informed by the variable selection process, as well as by stakeholder desires. The environment allows for decision makers to size vehicles based on the missions they input, analyze the trade offs of technologies, and also allow for off-design analysis. Accomplishing this task involved the creation of visual elements for results displaying, software creation to allow direct access to NDARC from within the environment, and other features.

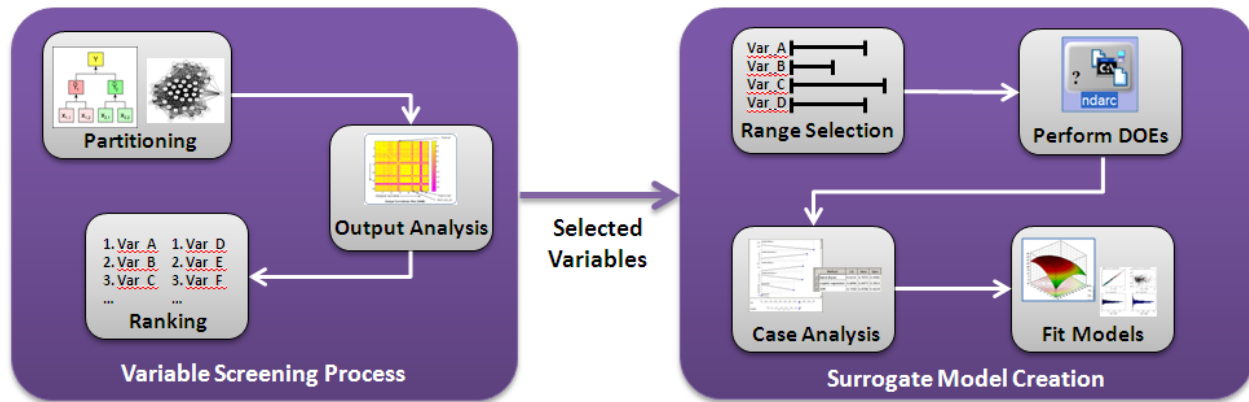


Figure 8 JMR Surrogate Modeling for CATE Process Flow

The surrogate model creation phase of the first fork met some difficulties in maintaining a high percentage of successful DOE cases for NDARC. On average, the number of cases for each design was around 1,750, but around 50% of those would be “failed” cases. A failed case either did not converge to a solution, or created a solution that had infeasible properties, such as an erroneous fuel weight.

Improvement of the NDARC case initial guesses was attempted by inputting previous trim solutions as initial guesses, and this provided some portion of the successful cases. A surrogate model was fit to the control positions that were found from the successful cases and used as an input to the NDARC model for the cases that had failed, but there were very few cases that succeeded due to that effort.

An analysis of the successful and failed cases was performed in order to determine if there were any patterns or features of the failed cases that could be used to improve the success rate. The analysis showed that there were no immediately obvious trends between failed and successful cases, as shown with a correlation analysis. A data classification analysis showed a moderate relationship between some mission and aerodynamic variables and the chance that a case would fail. However, the predictive power of these relationships was relatively poor, indicating a good chance that the failures had a random component.

Even with the failed cases, there was enough information in the successful cases to create surrogate models that represented NDARC well. Further research into failed cases was proposed for the research effort that this document will explain.

CATE Summary

The CATE tool was designed in Microsoft Excel, for ease of transfer, upgrade, and usability. The ubiquitous nature of Microsoft products, as well as the flexibility in provided by the VBA back-end makes this choice natural for a tool to be used by multiple stakeholders and analysts.

The tool contained two primary ‘dashboards’, or front-ends to the surrogate models and other data gathered from the efforts outlined in this report, shown in the figures below. The first dashboard, known as the ‘Sizing Dashboard’ contains many features, such as: mission definitions, sizing constraint definitions, technology parameters, and multiple forms of output and response plots for each concept.

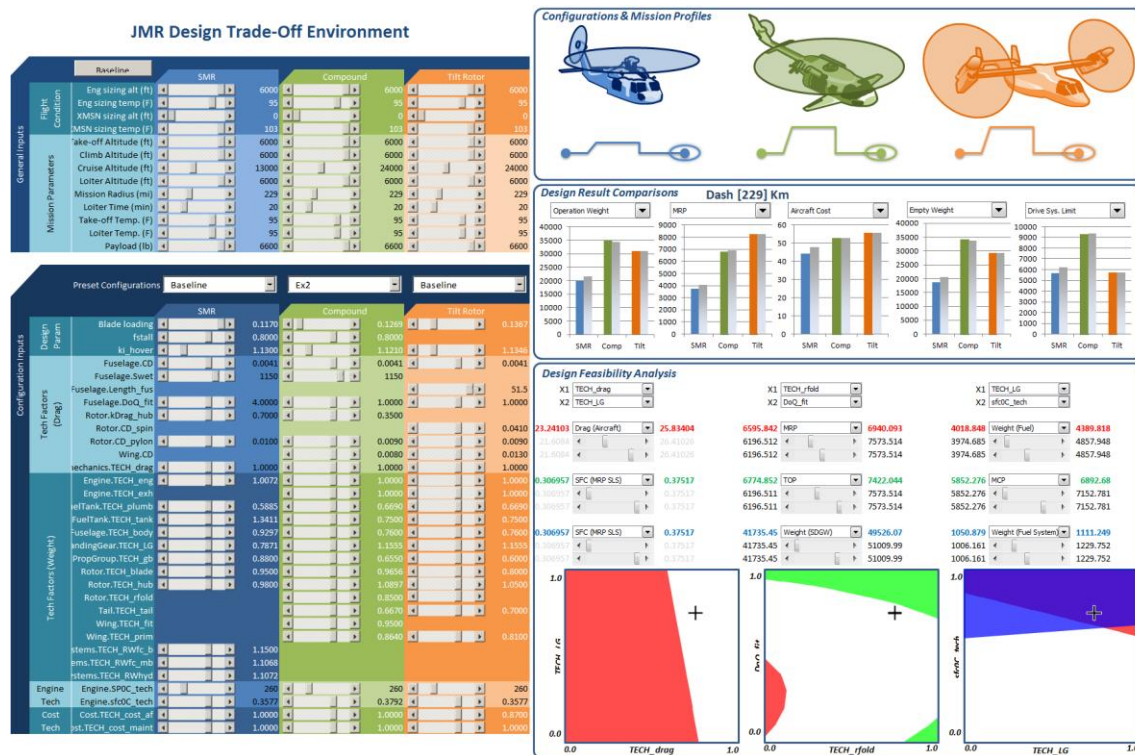


Figure 9 Captured Images of the Sizing Dashboard

The second dashboard is the ‘Off-Design Dashboard’, which receives fixed vehicle information from the Sizing Dashboard and analyzes the vehicle’s performance for off-design missions. Information given in the dashboard includes payload/range charts, point performance condition sweeps, and other data. This dashboard works by calling NDARC’s mission performance directly, through a custom software wrapper.

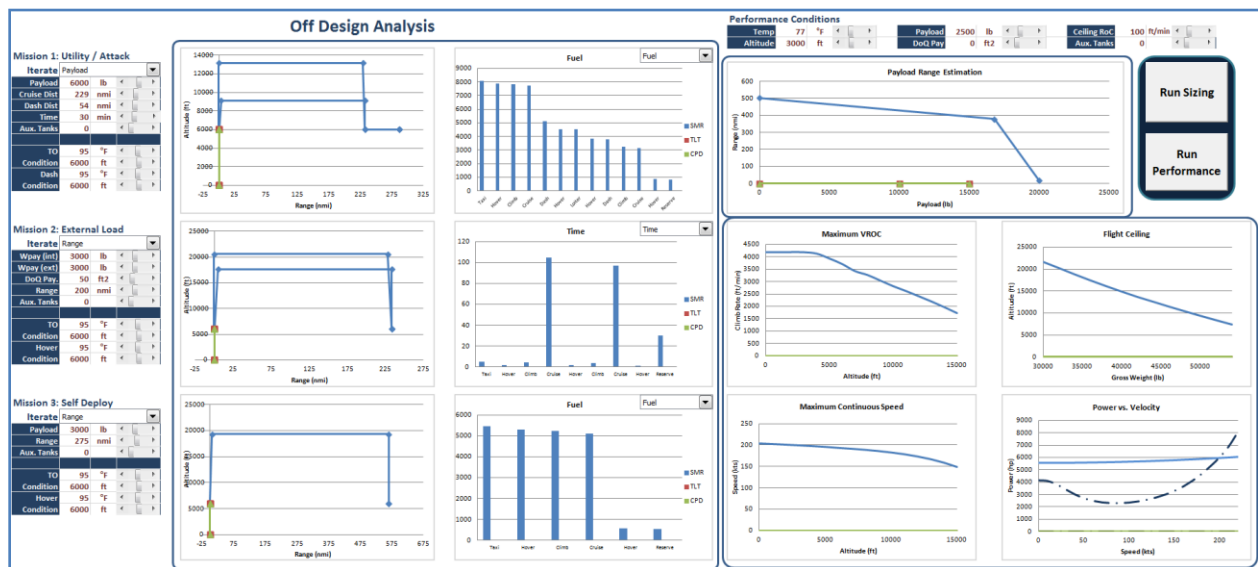


Figure 10 Captured Images of the Off-design Dashboard

Current Year Tasks and Results

The research effort that proceeded after the above summarized results was focused on increasing the capabilities of the CATE tool to provide users with a more streamlined user experience, more flexibility in using and updating information in the CATE, as well as with new features to enable technology portfolio assessment for both performance and mission effectiveness goals.

In addition to those stated goals, further research into analyzing failed cases and improving the surrogate models took place. This occurred alongside receiving updated JMR concept NDARC models. These new models were used to create updated surrogate models for the CATE tool, along with the addition of an input variable to directly account for accessory power usage due to new technologies.

The sections that follow will detail the research and CATE upgrade tasks that were accomplished in the current year. First, the failed case analysis and updated surrogate models will be discussed. The new models included a more general mission definition capability, which will be briefly outlined. Following that, the work done to enable the definition and assessment of JMR TD technologies is outlined. This includes the ability to define a technology's Mission Effectiveness, which can capture benefits and costs of a technology that NDARC was not designed to capture. A discussion of the research into technology portfolio selection as well as how to interpret and use the results will take place.

Following those sections, an outline of the improved CATE layout and functionality will be given. For a more detailed explanation of the new features, an updated User's Manual for CATE has been provided as an additional document.

Surrogate Model Creation

This section discusses the process of updating and analyzing the new NDARC surrogate models for the CATE tool. First, some minor changes to variables and their ranges were made. During the fitting of the models, several discoveries were made regarding the failed cases, which were used to greatly improve the rate of successful cases. Summaries of the new models are then given.

Variables and Ranges for Three Configurations

For the updated NDARC models that were received, the variables that are included in the CATE tool are given in Table A1, Table A2, and Table A3. The variable “Pacc_0” has been included, which models an accessory power draw. This gives a more direct way to model the power draw of technologies without having to modify engine parameters. The ranges of the variables are given in Table A4, Table A5, and Table A6. An additional change is that the range of SP0C_Tech, and engine specific power tech factor, was shifted to cover a lower set of values than previously. This was done to improve the amount of successful cases, as will be explained in the next section.

Wider ranges were given for the ‘improvement’ direction of technology factors, in order to give room to reflect potential future progress. A direction of improvement is considered to be lower weight, power, fuel usage, and drag. Some room is left for degradation of the factors, since there will inevitably be trade-offs within new technologies. Some ranges in the table are given as percent deviations from the baseline value, while others are given in absolute terms.

Once the variables and their ranges had been defined, the surrogate modeling process continued with the creation of the DoEs for experimental data, then with fitting the data. Based on the variable ranges given above, a set of DoEs was created using a randomized design. The extremes of the design ranges were investigated to ensure coverage at the edges of the design space, along with the great coverage of the interior. The DoEs were also made large, in order to provide some overhead for cases that might not be able to converge.

On average, the number of cases for each design was around 1,750. The large number of cases was selected, as mentioned previously, to help ensure that even with failed cases, there would be enough successful runs to create surrogates from.

Failed Case Analysis

With the new models, a high incidence of successful cases was observed in the DOE results. At least 80% of the cases run were successful overall, while some of the configurations had an even higher success rate. To achieve this high success rate a detailed investigation had

been performed which identified improvement opportunities. The end result is a higher confidence and increased efficiency when generating and running DOEs. However, a few failed cases are still expected.

The primary improvement opportunity was based on the engine technology factor ‘SP0C_tech’, which is an engine specific power scaling factor. The new NDARC models had exhibited a different failure behavior than the previous ones, and showed a high correlation of failed cases with a discrete jump in the resulting engine fuel consumption. For a failed case, the engine fuel consumption was set to the default value of the model, and not scaled with the technology factors. This was occurring because the SP0C_tech factor was becoming too large for the engine model. The tech factor had its range reduced in magnitude, which enabled a large number of successful cases. Other failed cases were mitigated by generalizing the mission definition, which is explained in a later section.

A brief investigation was performed to address the remaining failed cases. It was found that the convergence (success) of a case depends on the input estimate. The sensitivity of convergence versus an initial estimate (DGW) is shown in Figure 11. The x-axis is the initial DGW estimate, and the DGW and Fuel Weight outputs are displayed on the y-axis. It can be seen that the initial estimate used to seed the convergence scheme within NDARC can lead to either a successful or a failed case, while barely affecting the converged result. A similar behavior was observed with several other input variables, such as payload and flight speed. This indicates that the analysis conditions may require care when they are chosen to ensure convergence. In the case that further improvement is desired, beyond the current rates, a further analysis of the convergence characteristics could prove beneficial.

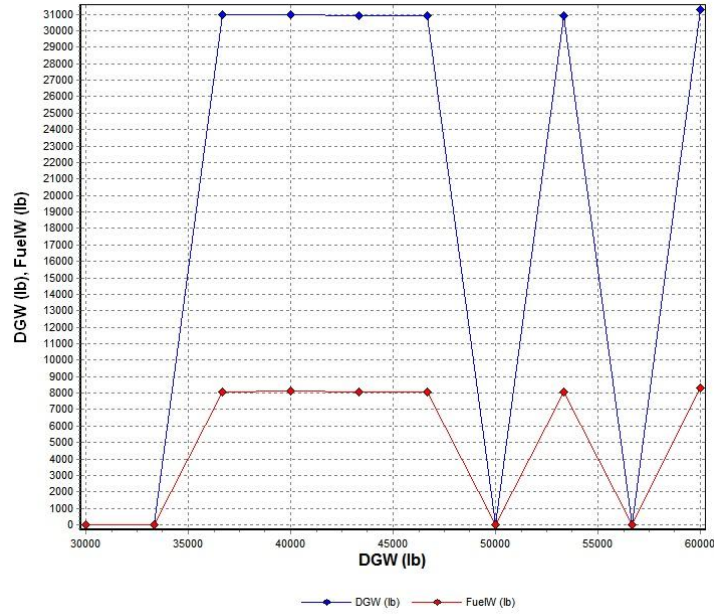


Figure 11 Convergence sensitivity to initial estimate

Given that such a large number of cases were successful, and that the remaining cause of failure is primarily based on the inherent instability in numerical solvers, the surrogate modeling can proceed with high levels of confidence that the surrogates will easily interpolate over the failed cases. This is because the regions of failed cases are still physically feasible, since they are the same regions as successful cases, but are numerically more unstable than the successful cases.

Surrogate Model Fitting

Modeling was performed in Matlab using Response Surface Equations (RSEs). Since the number of cases was very near the number of terms of a fully quadratic RSE with cross terms, stepwise regression was used to select the smallest model that still provided an acceptable level of accuracy. The statistics of the model fits are given below. First shown is an example fit plot for the Tilt Rotor's maximum takeoff weight function, see Figure 12. The training R² value shows a good fit to the 80% of the data that was used to train it. The Model Fit Error (MFE) and Model Representation Error (MRE) histograms show the distribution of the percentage error for

the fit and the validation cases, respectively. A standard deviation of 3 for the MRE cases means that 95% of the validation cases had an error within +/- 6%, or two sigma.

Further fit statistics are summarized in Table 1, Table 2, and Table 3 for the most important outputs of the models, as determined by the variable sensitivity and ranking analysis that was performed in a previous research year, along with the cost outputs. The columns of the tables are the MFE, in terms of R^2 , and MRE, in terms of the standard deviation of the percent error.

The fits can improve with further tuning of the models, as well as with increasing the number of successful cases from NDARC. Information from the analysis of failed cases will be used to inform that effort. Mitigation of the failed cases can occur simply by restricting the ranges of certain inputs to levels that do not cause a high probability of failure and by improving trim initial guesses.

The updated surrogate models are, in general, of a better quality than the previous models in the CATE tool. This is due to the further examination into improving model convergence and variable ranges that was undertaken during the research year.

Table 1 Fit Statistics for Compound Surrogate Models

Output	MFE (Training R^2)	MRE (Std. Dev of % error)
Weight_OpW	0.9851	1.972
Weight_SDGW	0.99084	1.5766
Weight_DGW	0.98952	1.6693
Weight_WMTO	0.99628	2.2413
Weight_UsefulLoad	0.98962	1.3274
Weight_WE	0.99148	1.7707
Engine_MRP	0.99655	3.6329
Engine_CRP	0.99655	3.6329
Cost_aircraft_cost	0.99001	2.1806
Cost_maintenance_cost	0.99064	2.1316

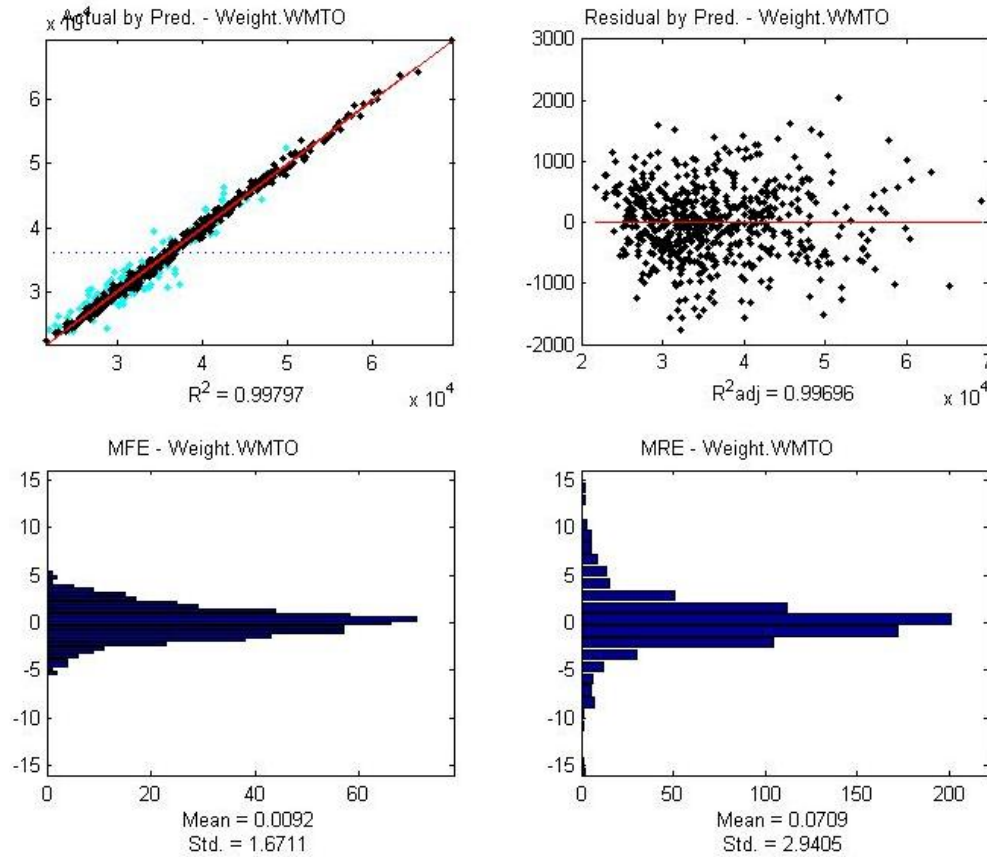


Figure 12 Sample Fit Statistics for Tilt Rotor WMTO RSE

Table 2 Fit Statistics For Tilt Rotor Surrogate Models

Output	MFE (Training R^2)	MRE (Std. Dev of % error)
Weight_OpW	0.99383	2.4142
Weight_SDGW	0.99371	2.2096
Weight_DGW	0.99353	2.2671
Weight_WMTO	0.99696	2.9405
Weight_UsefulLoad	0.99148	2.1877
Weight_WE	0.99452	2.5431
Engine_MRP	0.9782	12.9965
Engine_CRP	0.9782	12.9965
Cost_aircraft_cost	0.99347	4.5382
Cost_maintenance_cost	0.99338	5.8717

Table 3 Fit Statistics For SMR Surrogate Models

Output	MFE (Training R²)	MRE (Std. Dev of % error))
Weight_OpW	0.99706	2.1992
Weight_SDGW	0.99517	2.5543
Weight_DGW	0.99715	2.4928
Weight_WMTO	0.99654	3.3734
Weight_UsefulLoad	0.99577	2.9799
Weight_WE	0.99672	2.4054
Engine_MRP	0.99307	4.2967
Engine_CRP	0.99307	4.2968
Cost_aicraft_cost	0.99647	3.1587
Cost_maintenance_cost	0.99616	3.0859

With the creation of the surrogate models, the relationships between technologies, mission parameters, and requirement can now be updated within the Capability Assessment and Tradeoff Environment.

Generalized Mission Structure

JMR TD vehicle mission structures can come in a wide variety of forms, with different payload requirements, hover requirements, mission segment order, and other mission features. Capturing such a wide array of potential missions would require an infeasible amount of variables and cases to be run in NDARC. If a maximum of 10 mission segments was allowed, with an average of 4 variables needed for each segment (segment type, payload, atmosphere type, and engine operating characteristics), there would be more than 40 variables needed just for the mission definition. This is in addition to the nearly 40 variables needed to define the vehicle itself. Since mission segments could take on several different discrete values, and since mission performance is dependent on the sequence of mission segments, the dimensionality of the problem grows rapidly to an infeasible level for surrogate modeling.

Therefore, the research effort wants to provide the user with a general mission structure that can satisfy the standard forms of vehicle sizing missions while also providing the user with flexibility to generate a custom mission structure. Since different missions can be analyzed using

CATE's Off-Design analysis capabilities, a general sizing mission can both reduce the modeling effort for the surrogate models and improve their fit quality. Based on the sizing JMR TD missions, the primary structure is seen to be standard cruise out and back structure, with a loiter segment at the midpoint. Difficulty is added in sizing the engine to handle strict hover requirements as well.

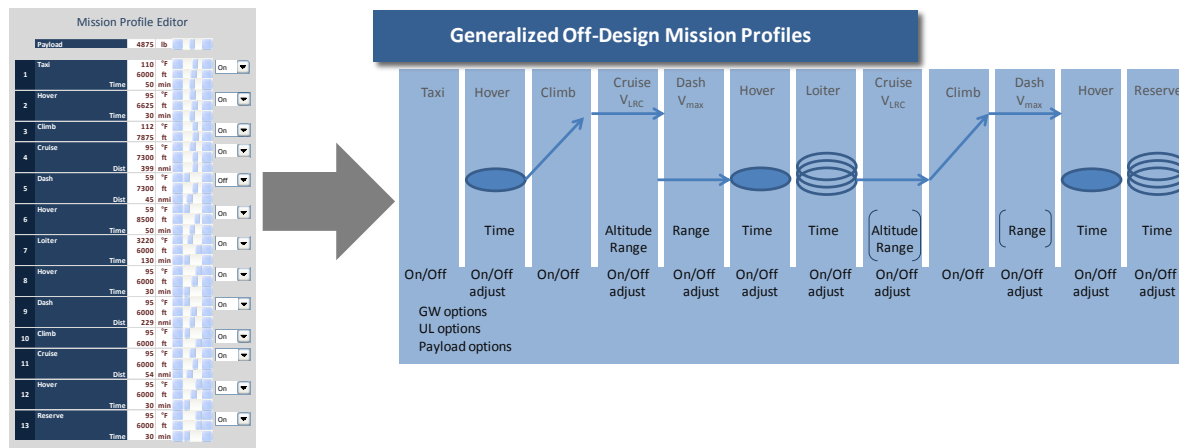


Figure 13 Generalized Mission Profile

The use of the general mission profile helped improve NDARC convergence by using a streamlined set of vehicle requirements. In addition to the general mission profile for sizing, a mission profile for off-design analysis was also created. This profile contains more features for the user to select and analyze. This functionality is detailed in the User's Manual for CATE. The combination of a general sizing mission profile that can size vehicles reliably with the Off-Design analysis capabilities enables the user to understand a JMR TD vehicle's performance in a wide range of conditions.

Technology Portfolio Definition and Assessment in CATE

Previously, the CATE tool did not contain the ability to define unique technologies, nor was it capable of assembling technologies into portfolios that could be analyzed or optimized. A

primary effort for the research was to add this capability on to the surrogate modeling and technology factors that have been updated and improved in the CATE.

Based on this need, the CATE tool now contains the ability to define technologies and then generate technology portfolios based on a particular set of objectives. An overview of the capabilities and their links are shown in Figure 14. Each capability will be explained in the following sections. The discussion begins with an overview of the capabilities, followed by a theoretical discussion regarding technology selection, which informs recommendations for using and interpreting the CATE's portfolio selection capabilities.

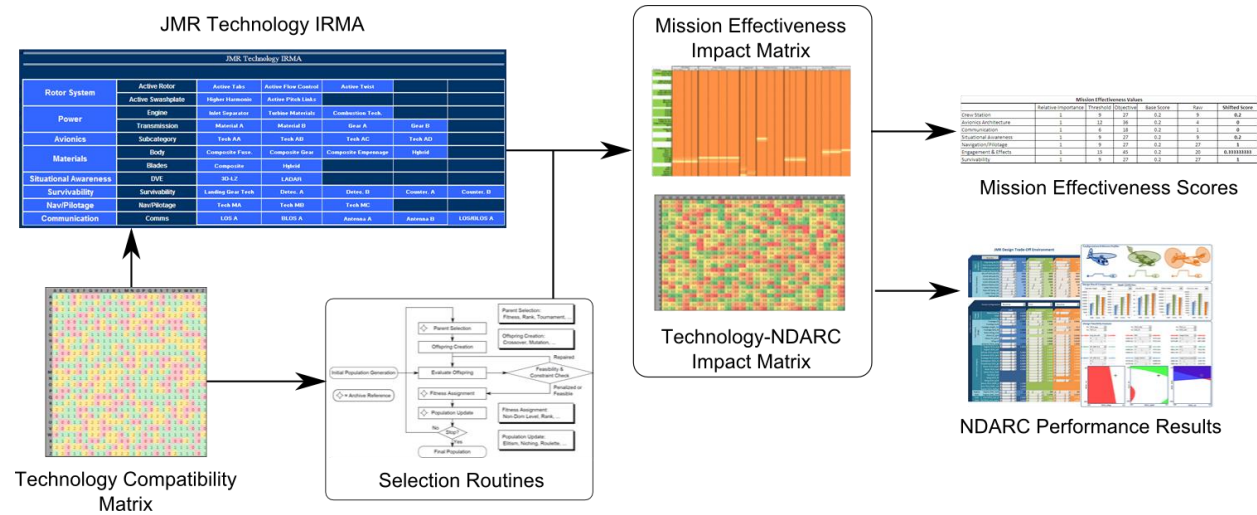


Figure 14: CATE Technology Portfolio Framework

Technology Definition in CATE

Technologies are made known to the CATE tool by defining them in the Interactive Reconfigurable Matrix of Alternatives (IRMA)^{xi}. The user can simply un-hide rows of the IRMA in the CATE tool in order to create new categories of technologies, or to grow an existing category. The boundaries of the IRMA can be seen from the pre-defined borders on the IRMA sheet. Within that range, up to 145 technologies can be defined. The initial version of the CATE has 36 example technologies, for the portfolio selection capabilities. The IRMA can be started by

pressing 'RUN'. When this is pressed, technologies can be selected, which will be colored green. Any technologies that are incompatible will be shown in red. The user can continue to select technologies and view the remaining feasible set of technologies. This process is shown in Figure 15 and Figure 16.

JMR Technology IRMA						
Rotor System	Active Rotor	Active Tabs	Active Flow Control	Active Twist		
	Active Swashplate	Higher Harmonic	Active Pitch Links			
Power	Engine	Inlet Separator	Turbine Materials	Combustion Tech.		
	Transmission	Material A	Material B	Gear A	Gear B	
Avionics	Avionics	Tech AA	Tech AB	Tech AC	Tech AD	
Materials	Body	Composite Fuse.	Composite Gear	Composite Empennage	Hybrid Emp.	
	Blades	Composite Blades	Hybrid Blade			
Situational Awareness	DVE	3D-LZ	LADAR			
Survivability	Survivability	IR Suppression	Detec. A	Detec. B	Counter. A	Counter. B
Nav/Pilotage	Nav/Pilotage	Tech MA	Tech MB	Tech MC		
Communication	Comms	LOS A	BLOS A	Antenna A	Antenna B	LOS/BLOS A

Run
Reset
Train
Save/Load Scenario

Figure 15: Selection of One Technology in the CATE IRMA

JMR Technology IRMA						
Rotor System	Active Rotor	Active Tabs	Active Flow Control	Active Twist		
	Active Swashplate	Higher Harmonic	Active Pitch Links			
Power	Engine	Inlet Separator	Turbine Materials	Combustion Tech.		
	Transmission	Material A	Material B	Gear A	Gear B	
Avionics	Avionics	Tech AA	Tech AB	Tech AC	Tech AD	
Materials	Body	Composite Fuse.	Composite Gear	Composite Empennage	Hybrid Emp.	
	Blades	Composite Blades	Hybrid Blade			
Situational Awareness	DVE	3D-LZ	LADAR			
Survivability	Survivability	IR Suppression	Detec. A	Detec. B	Counter. A	Counter. B
Nav/Pilotage	Nav/Pilotage	Tech MA	Tech MB	Tech MC		
Communication	Comms	LOS A	BLOS A	Antenna A	Antenna B	LOS/BLOS A

Run
Reset
Train
Save/Load Scenario

Figure 16: Selection of a Technology Portfolio in the CATE IRMA

The compatibility of technologies is controlled by a compatibility matrix. To define compatibilities, the 'Train' can be used to open a window that enables the user to select two technologies and define if they are compatible, incompatible, or 'must-have'. A 'must-have' technology relationship will cause the IRMA to automatically select additional technologies if

they must be selected with a different technology. These, and other aspects of using the IRMA, are explained in more detail in the provided User's Manual.

Technology Impact Definitions in CATE

The IRMA and the compatibility matrix only enable the user to view what kinds of portfolios may be possible, as well as explore the impacts of technology incompatibilities. The CATE also gives the user the ability to model technologies through the NDARC surrogate models, as well as through qualitative rankings of mission effectiveness, which is an additional new feature of the CATE. The Technology Impact Matrix (TIM) has technologies as rows, and NDARC surrogate model inputs as the columns. Each entry represents a percent change from the baseline value that the technology will impact. For example, a technology can be defined as decreasing a component's weight by 10% from the baseline value. In the sheet labeled 'TechAttributes', the user can edit these percent changes for their technologies. A partial example of the TIM is shown in Figure 17.

	Actual	Technology	CWs	fstall	Ki_hover	fSDGW
1	0	Active Tabs	0.1	0.1	0.2	
2	0	Active Flow Control	0.1	0.2	0	
3	0	Active Twist	0.05	0.2	0.1	
4	0		0	0	0	
5	0		0	0	0	
6	0	Higher Harmonic	-0.1	0.2	0	
7	0	Active Pitch Links	0.1	0.1	0.1	
8	0		0	0	0	

Figure 17 Partial Example Technology Impact Matrix (TIM)

Mission Effectiveness (ME) measures are based on different mission capability areas, as given in the Mission Systems Effectiveness Trades and Analysis (MS ETA) BAA^{xii}, which focuses on defining mission effectiveness for JMR TD technologies. The user can input a qualitative measure as to how much a technology meets a ME goal for each area. In general, a value of 1, 3, or 9 can be used to represent different levels of goal completion (such as low, medium, and high). This is similar to Quality Function Deployment (QFD) methods.

Due to the qualitative nature, though, the user is given the ability to define what they mean by those values. For each broad category of ME goals, the user can define what numbers mean threshold, and what numbers mean objective. The threshold is defined as the qualitative

level of goal completion that is a minimum requirement. The objective value is qualitative level of goal completion above which no more credit can be given. When technologies meet a threshold value, a score that is between 0 and 1 will be given to the portfolio. Once a portfolio reaches the objective, no bonus score will be given. This is shown graphically in Figure 18.

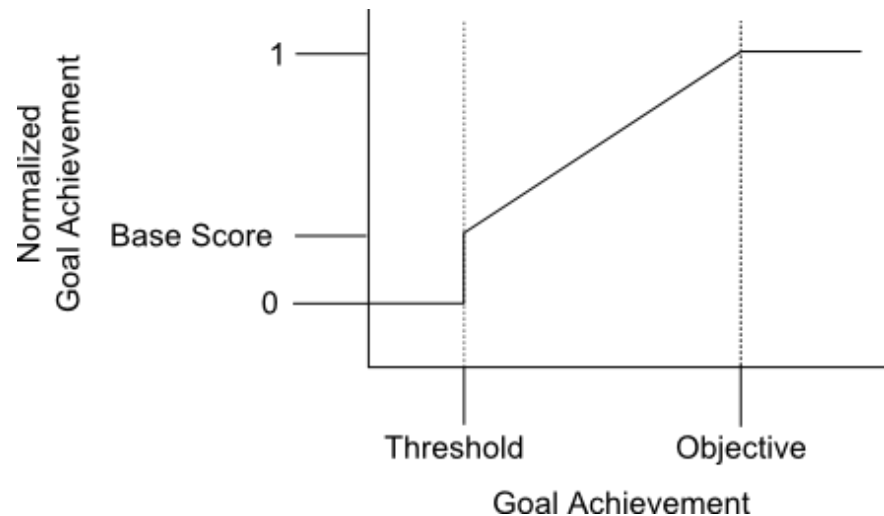


Figure 18: Qualitative Scoring for Mission Effectiveness

For example the user could define that a ME sub-category must have technologies selected in it such that the least amount of ‘value’ in the category was three. This could mean that one technology that is stated as having a ‘medium’ impact (3 in the QFD parlance) is selected, or 3 technologies that have a ‘low’ impact (a 1) are selected in order to meet that goal. If that goal is the threshold, then any impact in the category under 3 is not given any score, since even the minimum goal has not yet been met.

As soon as the minimum goal has been met, though, then some score can be given. This score is defined as the “Base Score”, and is defined by the user. As technologies are selected, and the impact in the category grows, it may reach and exceed an Objective value, which is a user-defined measure of impact that denotes a goal above which no more score will be given. In between the threshold and objective levels of impact, a linear increase in the score is output. The score that is output represents how close a set of technologies is to reaching the objective value for the ME category. A score of zero means that the threshold has not been reached. If the score

is the base score, then the threshold has just been achieved. Once the score is 100%, then the objective goal has been completely attained.

The output of the mission effectiveness analysis is shown in Figure 19, for when no technologies are selected. The user is allowed to modify the threshold, objective, and base score values. The shifted score represents the percent of goal attainment that has been realized for a given ME category. This system of qualitative ranking allows the user to understand how close a portfolio gets to achieving a goal, on a uniform scale for each MS category, based on the user's explicitly defined goals. This is also highly transparent, which is beneficial for qualitative assessment, since users may have different preferences or goals.

	Mission Effectiveness Values				
	Threshold	Objective	Base Score	Raw	Shifted Score
Crew Station	3	18	0.2	0	0%
Avionics Architecture	4	24	0.2	0	0%
Communication	2	12	0.2	0	0%
Situational Awareness	3	18	0.2	0	0%
Navigation/Pilotage	3	18	0.2	0	0%
Engagement & Effects	5	30	0.2	0	0%
Survivability	3	18	0.2	0	0%

Figure 19: Mission Effectiveness Outputs

The IRMA contains a visualization of the ME output as well, as shown in Figure 20. In the graph shown below the IRMA, the user can see how close a set of technologies is to achieving the defined objective for a ME category. Note that the technologies shown in the IRMA are only for example.

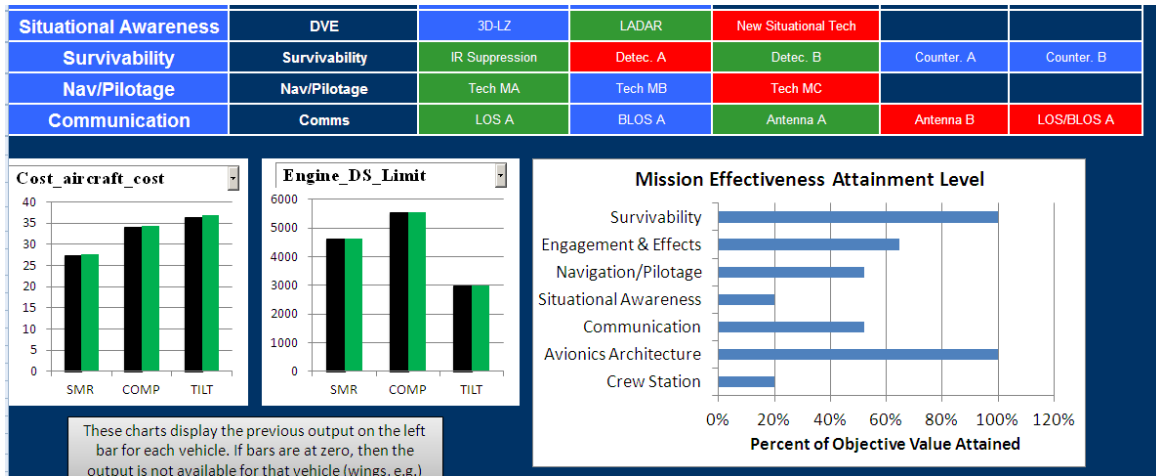


Figure 20: Mission Effectiveness Output with IRMA

Technology Impact Definitions in CATE

The primary capability of the different CATE technology assessment features is the ability to have the CATE tool select technology portfolios for the user, based on user-defined goals. In the sheet labeled 'Technology Selection', the user is presented with two options that control the algorithm, as well as a choice of vehicle to base the selection on, and outputs to define goals for. These goals can either be to 'Minimize', 'Maximize', or 'Ignore'. Once the goals are defined, the 'Run' button can be used. The meaning of the options (population and generations) are given in the following sections). A screenshot of these features is shown in Figure 21.

Technology Selection through GA		
Selection Parameters		
Population Size:	50	
Generation Count:	100	
Objective Function Options		
Vehicle Type:	SMR	
Outputs		
Output Variable	Usage	
Cost (Aircraft)	Minimize	
Cost (Maintenance)	Minimize	
CRP	Ignore	
Drag (Aircraft)	Ignore	
Drag (Fuselage)	Ignore	

Run

Figure 21: Partial Screenshot of Technology Portfolio Selection Front-End

The algorithm that is used is the Non-Dominated Sorting Genetic Algorithm II (NSGAI) of Deb^{xiii}. As explained in the following section, this is a standard choice for discrete optimization of choices, such as technology selection. The NSGAI algorithm finds the Pareto Frontier of technology portfolios, given the objectives that have been defined. This concept will be defined further below, but it simply means that it finds the set of portfolios that represents a pure trade-off between desired objectives. On the Pareto Front, no performance can be gained without a loss in some other performance.

The algorithm is implemented through the Inspyred Python library^{xiv}, which is a free, open source framework for creating biologically-inspired computational intelligence algorithms. It is compiled to an executable that runs on Windows XP or newer machines. When the algorithm completes, a new sheet is created with the results. The sheet is named based on the date and time that the algorithm was run. The results are given in a table of technology portfolios. In this table, the user can see which technologies are selected or not for each portfolio, as well as view the performance of the portfolio. Graphs of the relationships between the different selected goals are also shown. An example output is shown in Figure 22. Note that each point is labeled with the portfolio number, which can be used to find the portfolio in the results table.

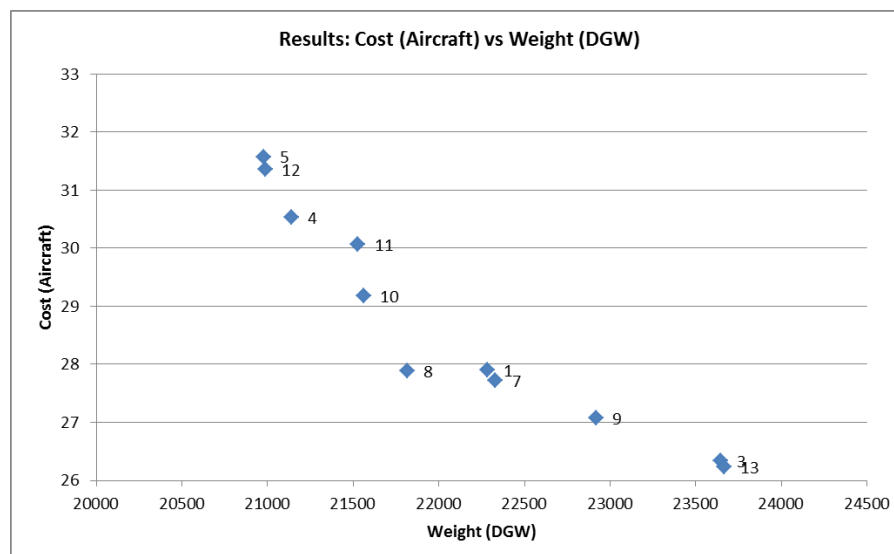


Figure 22: Example of an Output Pareto Frontier

The last set of information in the results sheet is a ranking of each technology. These rankings are based on the frequency of a technology being present on the Pareto Front. The more often a technology shows up on the Pareto Front, the more important it is likely to be for future funding and research. While the selection of a portfolio from the Frontier is beyond the scope of this document, a technology that appears frequently on the front is likely to be important, since it can likely help satisfy a wide range of goals. A more in-depth explanation of interpreting and understanding the results of the Portfolio Selection algorithm is given after the algorithm is explained.

Genetic Algorithms for Technology Selection in CATE

This section will discuss the concepts and algorithm that is used for technology portfolio selection in the CATE tool. It will first explain the general concepts of multi-objective optimization, followed by the particulars of genetic algorithms. The interpretation of the algorithms' results is discussed at the end of this section.

Multi-Objective Optimization Overview

Before discussing the algorithm used to select portfolios, some key concepts for multi-objective optimization will be discussed. Since there may be multiple, competing objectives, fitness may no longer be defined in terms of just one objective. Rather, the trade-off between competing objectives must be quantified for computer algorithms. The trade-off is captured with the concept of dominated and non-dominated solutions. First, the multi-objective problem is based on a function that returns a set of p objectives that are solved for a given feasible solution, x , along with a set of m constraints on either the inputs or outputs, as shown in the problem formulation below. Notice that minimization is assumed for convenience, without a loss of generality.

$$\begin{array}{ll} \text{minimize} & F(x) = (f_1, f_2, \dots, f_p) \\ \text{subject to} & g_i(x, F) \leq 0, \quad i \in \{1, 2, \dots, m\} \end{array}$$

From this problem statement, where f_i 's are the individual objectives that result from a feasible point, x , the concepts that lead to Pareto Optimality are defined below.

Pareto Dominance:

A solution, $y = F(x)$, is said to **dominate** another solution, $y' = F(x')$, if and only if the following condition is met:

$$y < y' \Leftrightarrow y_i \leq y'_i \quad \forall i \in \{1, \dots, p\} \wedge y \neq y'$$

The solution, y' is then said to be **dominated**. The solution, y , will sometimes be referred to as **non-dominated**. The preference relation, $<$, is referred to as dominance.

Pareto Frontier:

A set of solutions, Y , is said to comprise a **Pareto Frontier**, or be non-dominated if the following conditions are met:

$$\{\forall y \in Y : \neg \exists y' \in Y - \{y\} \ni y < y'\}$$

Which says that no solution in Y is dominated by any other solution in Y . A set being a pareto frontier does not imply that it is the *true* pareto frontier of the problem, F .

Those statements can be summarized in the following way. First, Pareto Dominance simply means that one solution is better (as defined by the decision maker) or equal to another solution in all objectives. A Pareto Frontier is a set of solutions that are all non-dominated. This means that no two points are better in all areas than another. On the Pareto Front, if improvement in one objective is desired, then some other objective must necessarily be diminished (if they are competing objectives). These concepts are used in algorithms to maintain a set of points that are the best possible set of points, given the objectives that have been defined.

Technology Selection with Genetic Algorithms

Genetic Algorithms (GAs) are a generic class of algorithms that optimize discrete and continuous multi-objective functions by using the properties of evolution and natural selection to guide the optimization. They are used extensively for a wide variety of problems, most relevantly for the knapsack problem^{xv} and technology and portfolio optimization and selection^{xvi,xvii,xviii,xix}. A general template for GAs, which references standard GA operators, is given in Figure 23.

The solutions represent a technology portfolio, which is just a set of technologies. In GAs, a solution is generally called a 'chromosome', which is made up of 'genes'. Each gene represents a particular variable or input to an optimization problem. For technology selection, each technology is represented by a gene that is either 0 or 1. A 0 means that the technology is not included, while a 1 means that it is included in the set. This is called a binary chromosome, and is shown in Figure 7, for a notional technology portfolio with n technologies. Notice that technologies 1 and $n - 1$ are selected for the portfolio.

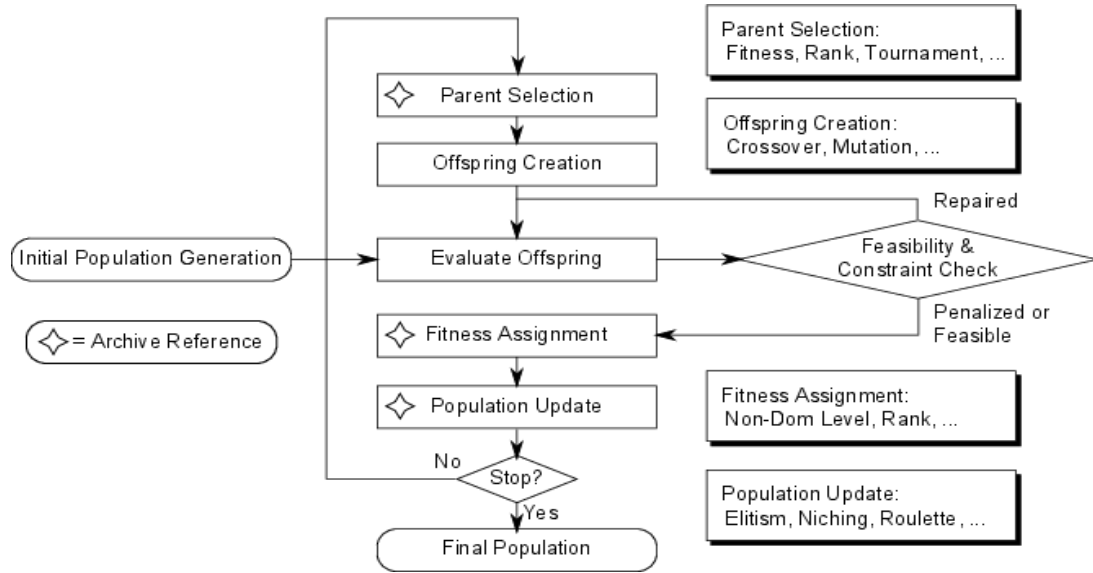


Figure 23: General Genetic Algorithm Framework

Table 4 Example binary chromosome format for GA

1	0	...	1	0
t_1	t_2	...	t_{n-1}	t_n

The general framework starts with the creation of a 'population' of possible solutions to an optimization problem. In the CATE tool, this population is created randomly. The population is evaluated using the TIM and surrogate models of NDARC in the CATE tool. During the evaluation, the compatibility of the technologies is tested using the IRMA's compatibility matrix.

If a technology is causing an incompatibility to arise, then it is removed from the portfolio. Since there will be at least two technologies that are incompatible (compatibilities are defined reciprically), a decision must be made about which of the incompatible technologies to remove from the portfolio. The choice of the technology to be removed is made at random, which prevents any bias from entering the algorithm. Once the population has been made feasible, then its fitness is evaluated. This evaluation is based on how dominated each solution is. Points that are not dominated, or weakly dominated, are carried over to the next stage of the algorithm.

Genetic Algorithms mimic nature, in that they select parents to create new solutions from. In the context of technology portfolios, two portfolios are chosen to be parents based on some fitness criteria. For example, two points that are far away on the Pareto front may be selected to be parents. Offspring are then created, which is done by sharing information between the parents. The most common procedure is that a portion of the chromosome from one parent will be given to the other, and vice versa. This is done to try to combine the good parts of each parent (such as good technologies) to create an even better technology portfolio. Once a set of offspring are created, their fitness is evaluated, and the process continues until some termination criteria is met.

The NSGAI algorithm maintains an archive of non-dominated solutions, and attempts to 'push' the Pareto Frontier out until it nears the true Pareto Frontier. This push is accomplished by creating new solutions from combinations of existing good solutions, and with random changes to solutions to help explore the set of options.

The two parameters for the NSGAI algorithm that are presented to the user are the size of the population, and the number of generations. The larger these numbers are, the more options the GA will explore. This will increase the chances that the final Pareto Frontier is closer to the true frontier. However, this will increase the algorithm's run time. The population size is the number of parents to evaluate during each generation. The number of generations is the number of times that the algorithm creates new solutions.

Interpreting Technology Selection Results

Interpreting and using the results of a multi-objective Genetic Algorithm is different than interpreting the results of standard numerical optimizers. Unlike the more common numerical optimization, GAs do not provide results that are guaranteed to be a global optimum. There are no local derivatives for a discrete technology selection problems to check for optimality. Genetic Algorithms are stochastic algorithms, meaning that their results and performance are based on some random behaviors. This randomness is what gives the GA its power to explore new solutions. It also causes the interpretation of the results to change. Each run of the algorithm will likely return different results but, if the population and generation count is high, then the results are more likely to be the same between different runs.

It is critical to remember that the results of the algorithm are not necessarily the 'best' options. They are simply the best that were found during the algorithm's run. Research into the NSGAII has shown that it does provide high-quality results when given enough time to run. The base options of a population size of 50 and 100 generations are made to be a balance between the quality of the results and runtime, with a preference to results quality. When examining the results, the user is encouraged to not think of them as 'ideal' technology portfolios, but rather as technology portfolios that contain valuable technology combinations, relative to most other portfolios.

When finding Pareto Frontiers, there is the final problem that a user may wish to select a single point from the frontier to be the 'best' point. Based on the definition of the Pareto Frontier, this task cannot be completed without first defining the preferences of the user. These preferences must capture the relative values of each objective in order to decide which objectives are more important. This is currently beyond the scope of the CATE tool. This issue is presented in order to orient the user to the capabilities of the tool, as well as the limitations.

For the purposes of technology assessment, though, finding the Pareto Frontier is generally sufficient. The technologies that make up the designs on the frontier are likely to be the best ones to consider for more research, if the objectives considered are the most important to the user. This is why the CATE tool returns a ranking of technologies based on how often they occur

in the final Pareto Frontier. A technology that shows up very often indicates that it is able to balance competing objectives well. A technology that doesn't show up often may be a 'thoroughbred' that is very good at optimizing a single objective at the cost of the others. A careful examination of the technologies that are present will illustrate to the user how vehicle performance and effectiveness can be optimized, according to their goals.

Technology Selection Summary

These sections have reviewed the features and concepts related to the new technology portfolio selection capabilities in the CATE tool. Genetic Algorithms are used to analyze the user-defined technologies to find the Pareto Frontier of technology portfolios that can attempt to meet the goals of a stakeholder. Further details of the options available to the user are given in the CATE User's Manual.

Additional CATE Features and Upgrades

A series of modifications to the CATE tool took place during the research period. These modifications were made to improve usability, and were based on feedback from the involved stakeholders. The primary dashboard, which contains the features described in the previous work section, has been improved in the following ways, and as shown in Figure 24. The various features will be outlined here, and the reader is referred to the CATE User's Manual for a more detailed description of the specific ways of using the new features.

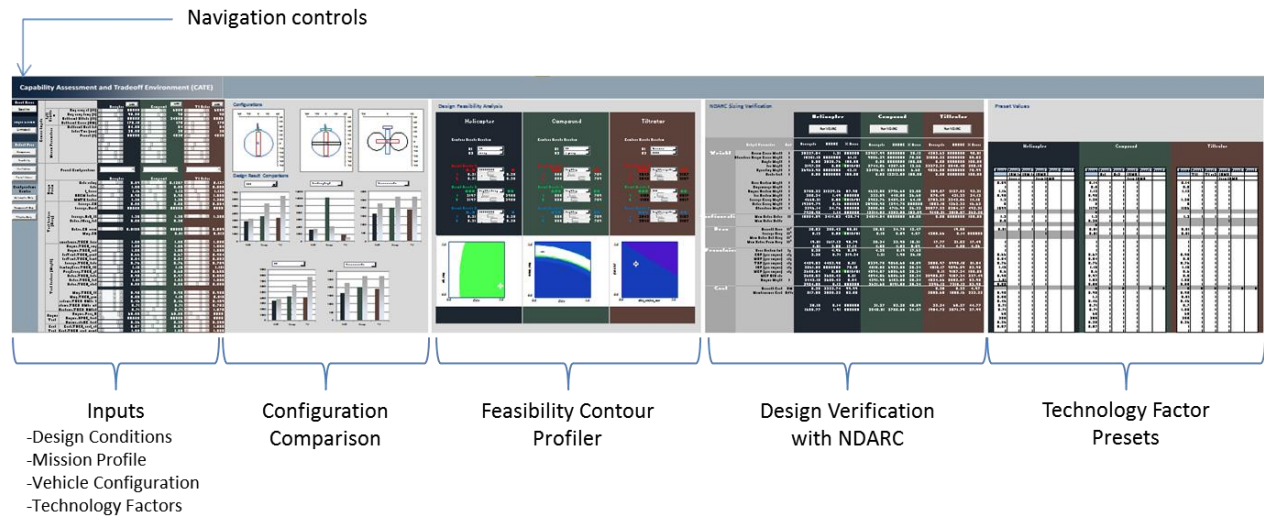


Figure 24 Captured Images of the Sizing Dashboard

First, the user is now given navigation controls, which enable the user to only view specific capabilities of the CATE dashboard at any given time. This has been done to allow users to only view the portions of the tool that they are concerned with, while limiting extraneous information. The user can show only one of the different CATE capabilities at a time, if they choose. They can also select to view only the capabilities for a given concept type. These enable the user to focus in on concepts or comparisons that are the most relevant to them.

The Off-Design Analysis dashboard has also been updated, as shown in Figure 25. The user can select the parameters for different mission segments, as discussed in the general mission definition section, and then use NDARC to generate various performance plots, such as Payload-Range and Vertical Rate of Climb charts as before.

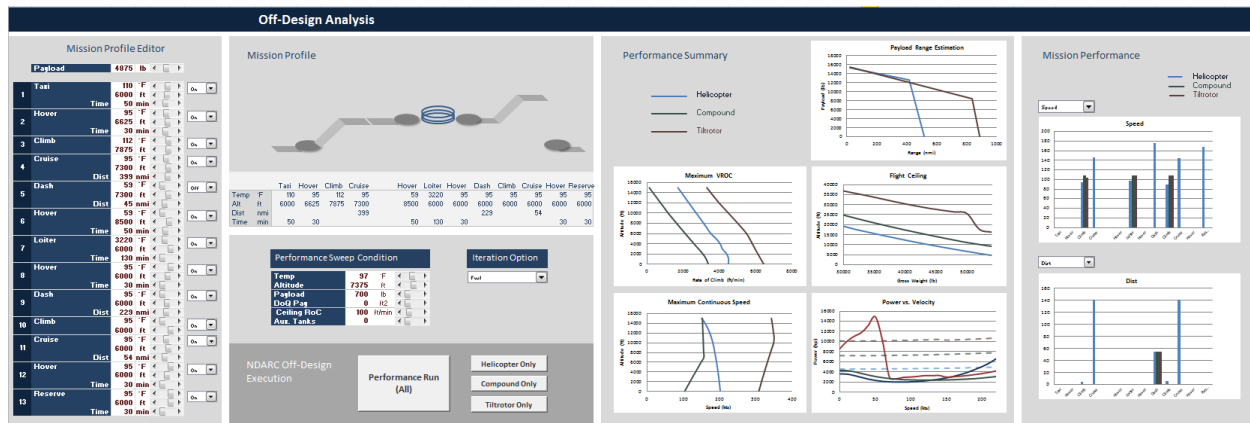


Figure 25: Captured Image of the Off-Design Analysis Dashboard

In addition to changes in the dashboards, there are new capabilities that enable the user to update the surrogate models in the CATE tool with new models that the user has created. This is important for any vehicle and technology assessment tool, since it allows the tool to remain a living capability that can update as requirements and information may change about the various concepts that are being examined. These capabilities are detailed in the CATE User's Manual, and they require the user to run DOEs and build surrogates of their model.

Summary and Conclusions

The work presented was done to expand upon the capabilities that already existed in the Capability Assessment and Tradeoff Environment (CATE) tool for the JMR TD effort. This work included the inclusion of new NDARC models, which forms the basis of the analysis capabilities of CATE, new abilities to define and analyze technologies, generic mission definitions, and new feature upgrades for the CATE tool.

Research had been continuing into the causes and solutions for the NDARC failed cases, the ultimate result of which was the understanding of the impact of extremely optimistic engine technology parameters, as well as the inherent limitations of numerical optimization within a sizing code. Both issues, once identified, were mitigated through various means, such as input variable range changes, and by slightly perturbing a failed case to enable the solution to converge. This provided a large set of successful cases that was used to build accurate surrogate models for

the CATE tool. Future work in this area would be to work with the NDARC source directly, or to add capabilities to the ModelCenter environment to automatically detect and perturb a failed case in a structured manner.

Once the number of successful cases was greater than 80% of the size of the DOEs, surrogate models were fit, which had overall better fit properties than previous surrogate models for CATE. The surrogate modeling was done using Stepwise Regression to fit Response Surface Equations, which enabled a reduction in the size of the equations, while still maintaining a high level of accuracy.

A more general mission structure was implemented in the surrogate models for vehicle sizing, as well as for off-design performance analysis. The former enabled more stable sizing runs, which improved the number of successful NDARC cases, while the latter provides the user with enhanced analysis capabilities once an interesting design point has been found. These mission structures capture the essential requirements and missions of potential JMR TD vehicles, while balancing surrogate model accuracy and feasibility.

To further expand the abilities of the CATE tool, technology definition and selection capabilities were added. The user of CATE can now define technologies, their compatibilities, and their impacts on NDARC inputs. This provides a traceable link between technologies and JMR TD vehicle assessment and design. Additionally, qualitative mission effectiveness assessment has been added, which is based on JMR TD mission systems definitions. In this way, technologies that generally just add weight and power to the vehicle can also be assessed for their primary purpose, which is modifying non-performance mission capabilities.

Technology portfolio selection capabilities have also been added. The user can, given that they have defined a set of potential technologies, define their preferences for metrics of concern and their directions of improvement. Using state of the art genetic algorithms, the CATE tool will find technology portfolios that represent a pure trade-off between the objectives of interest.

These portfolios can be further analyzed for trends and similarities that can inform the decision maker as to what technology programs may be the most valuable to pursue.

Finally, several upgrades have been made to the CATE environment to improve its usability. This includes allowing the user to view only the capabilities that they are concerned with, as well as new features for quickly updating the surrogate models. The research has improved the CATE tool's functionality, models, and increased the number of capabilities available to the user to assess vehicle concepts and the technologies that may improve them.

These improvements and new capabilities are central to the goal of supporting Quantitative Technology Assessment (QTA) for the JMR TD IPT. The tool provides the ability to perform the key steps of a QTA process, which are to define candidate technologies, link them to modeling and simulation of the systems of concern, and then use both user and optimization guided methods and visualizations to understand the impact of technologies. The results can be used to understand where capability gaps exist, as well as inform decision makers as to the best avenues of future technology and design efforts. Overall, the CATE tool and its processes have advanced to become a more comprehensive solution that enables QTA for JMR TD concepts and technologies.

Appendix

Variable Selection Tables

Table A1: Single Main Rotor: Selected Variables

Category	Variable	Description
Flight Condition	Condition.alt_eng	Altitude for Engine sizing condition
	Condition.temp_eng	Temp for Engine sizing condition
Mission Parameter	Mission.alt_cruise_out	Altitude @outbound cruise
	Mission.alt_cruise_in	Altitude @inbound cruise
	Mission.dist_cruise_out	Outbound cruise distance
	Mission.dist_cruise_in	Inbound cruise distance
	Mission.dist_dash_out	Outbound dash distance
	Mission.dist_dash_in	Inbound dash distance
	Mission.time_loiter	Midpoint loiter time
	Wpay.Wpay_dgw	Payload for DGW condition
	Wpy.Wpay_eng	Payload for Engine sizing condition
	Wpay.Wpay_mission	Payload for Mission profile
Design Parameter	Design.CWs	Blade loading
	Design.fstall	Constant in stall drag increment
	Design.Ki_hover	Induced velocity factor @hover
	Design.fSDGW	SDGW factor
	Design.fWMTO	WMTO factor
Drag	Drag.CD	Fuselage forward flight drag coefficient
	Drag.Swet	Fuselage wetted area
	Drag.DoQ_fit	Fixtures and Fittings DoQ
	Drag.kDrag_hub	Rotor hub forward flight square-cubed factor
	Drag.CD_pylon	Rotor pylon drag coefficient
	Drag.Wing_CD	Wing CD
	Drag.TECH_drag	Tech factor for profile power
Weight	Weight.TECH_eng	Tech factor for engine weight
	Weight.TECH_exh	Tech factor for exhaust system weight
	Weight.TECH_plumb	Tech factor for plumbing weight
	Weight.TECH_tank	Tech factor for fuel tank weight
	Weight.TECH_body	Tech factor for fuselage weight
	Weight.ECH_LG	Tech factor for basic landing gear weight
	Weight.TECH_gb	Tech factor for gear box weight
	Weight.TECH_blade	Tech factor for blade weight
	Weight.TECH_hub	Tech factor for hub and hinge weight
	Weight.TECH_rfold	blade fold weight

	Weight.TECH_fit	
	Weight.TECH_prim	
	Weight.TECH_RWfc_b	Tech factor for rotary wing flight control (boosted)
	Weight.TECH_RWfc_mb	Tech factor for rotary wing flight control (control boost mechanisms)
	Weight.TECH_RWhyd	Tech factor for rotary wing flight control hydraulics
Propulsion	Propulsion.Pacc_0	Accessory power
	Propulsion.SP0C_tech	Tech factor for specific power at MCP
	Propulsion.sfc0C_tech	Tech factor for specific fuel consumption at MCP
Cost	Cost.TECH_cost_af	Tech factor for airframe cost
	Cost.TECH_cost_maint	Tech factor for maintenance cost

Table A2: Compound: Selected Variables

Category	Variable	Description
Flight Condition	Condition.alt_eng	Altitude for Engine sizing condition
	Condition.temp_eng	Temp for Engine sizing condition
Mission Parameter	Mission.alt_cruise_out	Altitude @outbound cruise
	Mission.alt_cruise_in	Altitude @inbound cruise
	Mission.dist_cruise_out	Outbound cruise distance
	Mission.dist_cruise_in	Inbound cruise distance
	Mission.dist_dash_out	Outbound dash distance
	Mission.dist_dash_in	Inbound dash distance
	Mission.time_loiter	Midpoint loiter time
	Wpay.Wpay_dgw	Payload for DGW condition
	Wpy.Wpay_eng	Payload for Engine sizing condition
	Wpay.Wpay_mission	Payload for Mission profile
Design Parameter	Design.CWs	Blade loading
	Design.fstall	Constant in stall drag increment
	Design.Ki_hover	Induced velocity factor @hover
	Design.fSDGW	SDGW factor
	Design.fWMTO	WMTO factor
Drag	Drag.CD	Fuselage forward flight drag coefficient
	Drag.Swet	Fuselage wetted area
	Drag.DoQ_fit	Fixtures and Fittings DoQ
	Drag.kDrag_hub	Rotor hub forward flight square-cubed factor
	Drag.CD_pylon	Rotor pylon drag coefficient
	Drag.Wing_CD	Wing CD
	Drag.TECH_drag	Tech factor for profile power
Weight	Weight.TECH_eng	Tech factor for engine weight
	Weight.TECH_exh	Tech factor for exhaust system weight

	Weight.TECH_plumb	Tech factor for plumbing weight
	Weight.TECH_tank	Tech factor for fuel tank weight
	Weight.TECH_body	Tech factor for fuselage weight
	Weight.ECH_LG	Tech factor for basic landing gear weight
	Weight.TECH_gb	Tech factor for gear box weight
	Weight.TECH_blade	Tech factor for blade weight
	Weight.TECH_hub	Tech factor for hub and hinge weight
	Weight.TECH_rfold	blade fold weight
	Weight.TECH_fit	
	Weight.TECH_prim	
	Weight.TECH_RWfc_b	Tech factor for rotary wing flight control (boosted)
	Weight.TECH_RWfc_mb	Tech factor for rotary wing flight control (control boost mechanisms)
	Weight.TECH_RWWhyd	Tech factor for rotary wing flight control hydraulics
Propulsion	Propulsion.Pacc_0	Accessory power
	Propulsion.SPOC_tech	Tech factor for specific power at MCP
	Propulsion.sfc0C_tech	Tech factor for specific fuel consumption at MCP
Cost	Cost.TECH_cost_af	Tech factor for airframe cost
	Cost.TECH_cost_maint	Tech factor for maintenance cost

Table A3: Tilt-Rotor: Selected Variables

Category	Variable	Description
Flight Condition	Condition.alt_eng	Altitude for Engine sizing condition
	Condition.temp_eng	Temp for Engine sizing condition
Mission Parameter	Mission.alt_cruise_out	Altitude @outbound cruise
	Mission.alt_cruise_in	Altitude @inbound cruise
	Mission.dist_cruise_out	Outbound cruise distance
	Mission.dist_cruise_in	Inbound cruise distance
	Mission.dist_dash_out	Ounbound dash distance
	Mission.dist_dash_in	Inbound dash distance
	Mission.time_loiter	Midpoint loiter time
	Wpay.Wpay_dgw	Payload for DGW condition
	Wpy.Wpay_eng	Payload for Engine sizing condition
	Wpay.Wpay_mission	Payload for Mission profile
Design Parameter	Design.CWs	Blade loading
	Design.fstall	Constant in stall drag increment
	Design.Ki_hover	Induced velocity factor @hover
	Design.fSDGW	SDGW factor
	Design.fWMTO	WMTO factor
Drag	Drag.CD	Fuselage forward flight drag coefficient
	Drag.Swet	Fuselage wetted area

	Drag.DoQ_fit	Fixtures and Fittings DoQ
	Drag.kDrag_hub	Rotor hub forward flight square-cubed factor
	Drag.CD_pylon	Rotor pylon drag coefficient
	Drag.Wing_CD	Wing CD
	Drag.TECH_drag	Tech factor for profile power
Weight	Weight.TECH_eng	Tech factor for engine weight
	Weight.TECH_exh	Tech factor for exhaust system weight
	Weight.TECH_plumb	Tech factor for plumbing weight
	Weight.TECH_tank	Tech factor for fuel tank weight
	Weight.TECH_body	Tech factor for fuselage weight
	Weight.ECH_LG	Tech factor for basic landing gear weight
	Weight.TECH_gb	Tech factor for gear box weight
	Weight.TECH_blade	Tech factor for blade weight
	Weight.TECH_hub	Tech factor for hub and hinge weight
	Weight.TECH_rfold	blade fold weight
	Weight.TECH_fit	
	Weight.TECH_prim	
	Weight.TECH_RWfc_b	Tech factor for rotary wing flight control (boosted)
	Weight.TECH_RWfc_mb	Tech factor for rotary wing flight control (control boost mechanisms)
	Weight.TECH_RWhyd	Tech factor for rotary wing flight control hydraulics
Propulsion	Propulsion.Pacc_0	Accessory power
	Propulsion.SP0C_tech	Tech factor for specific power at MCP
	Propulsion.sfc0C_tech	Tech factor for specific fuel consumption at MCP
Cost	Cost.TECH_cost_af	Tech factor for airframe cost
	Cost.TECH_cost_maint	Tech factor for maintenance cost

Variable Range Tables

Table A4: SMR Variable Ranges

Variable	Baseline	Min	Max	Variable	Baseline	Min	Max
alt_eng	6000	4000	6000	Wing_CD			
temp_eng	95	59	103	TECH_drag	1	0.7	1.1
alt_cruise_out	14000	0	14000	TECH_eng	1	0.7	1.1
alt_cruise_in				TECH_exh	1	0.7	1.1
dist_cruise_out	175.1	157.59	227.63	TECH_plumb	0.655	0.4585	0.7205
dist_cruise_in				TECH_tank	0.839	0.5873	0.9229
dist_dash_out	54	48.6	70.2	TECH_body	0.759	0.5313	0.8349
dist_dash_in				ECH_LG	1.151	0.8057	1.2661
time_loiter	30	27	39	TECH_gb	0.601	0.4207	0.6611
Wpay_dgw	4020	4000	6600	TECH_blade	0.952	0.6664	1.0472
Wpay_eng				TECH_hub	1.009	0.7063	1.1099
Wpay_mission				TECH_rfold	0.85	0.595	0.935
CWs	0.0895	0.08055	0.11635	TECH_fit	0.95	0.665	1.045
fstall	1	0.7	1.1	TECH_prim	0.88	0.616	0.968
Ki_hover	1.16	1.05	1.25	TECH_RWfc_b	0.459	0.3213	0.5049
fSDGW	0.95	0.665	1.14	TECH_RWfc_mb	0.712	0.4984	0.7832
fWMTO	1.2	0.84	1.44	TECH_RWhyd	0.712	0.4984	0.7832
CD	0.0041	0.00287	0.00451	Pacc_0	60	42	66
Swet	1099	769.3	1208.9	SPOC_tech	200	120	260
DoQ_fit	1.2	0.84	1.32	sfcOC_tech	0.3577	0.25039	0.39347
kDrag_hub	0.5	0.35	0.55	TECH_cost_af	0.87	0.609	0.957
CD_pylon	0.01	0.007	0.011	TECH_cost_maint	1	0.7	1.1

Table A5: Compound Variable Ranges

Variable	Baseline	Min	Max	Variable	Baseline	Min	Max
alt_eng	6000	4000	6000	Wing_CD	0.008	0.0056	0.0088
temp_eng	95	59	103	TECH_drag	1	0.7	1.1
alt_cruise_out	24000	0	24000	TECH_eng	1	0.7	1.1
alt_cruise_in				TECH_exh	1	0.7	1.1
dist_cruise_out	175.1	157.59	227.63	TECH_plumb	0.655	0.4585	0.7205
dist_cruise_in				TECH_tank	0.839	0.5873	0.9229
dist_dash_out	54	48.6	70.2	TECH_body	0.759	0.5313	0.8349
dist_dash_in				ECH_LG	1.151	0.8057	1.2661
time_loiter	30	27	39	TECH_gb	0.601	0.4207	0.6611
Wpay_dgw	4020	4000	6600	TECH_blade	0.9652	0.67564	1.06172
Wpay_eng				TECH_hub	1.03	0.721	1.133
Wpay_mission				TECH_rfold	0.85	0.595	0.935
CWs	0.1367	0.12303	0.17771	TECH_fit	0.95	0.665	1.045
fstall	0.8	0.7	1.1	TECH_prim	1.095	0.7665	1.2045
Ki_hover	1.1346	1.05	1.25	TECH_RWfc_b	0.459	0.3213	0.5049
fSDGW	0.9544	0.66808	1.14528	TECH_RWfc_mb	0.712	0.4984	0.7832
fWMTO	1.25	0.875	1.5	TECH_RWhyd	0.712	0.4984	0.7832
CD	0.0041	0.00287	0.00451	Pacc_0	60	42	187
Swet	1170	819	1287	SPOC_tech	200	120	260
DoQ_fit	1.2	0.84	1.32	sfcOC_tech	0.3792	0.26544	0.41712
kDrag_hub	0.35	0.245	0.385	TECH_cost_af	0.87	0.609	0.957
CD_pylon	0.009	0.0063	0.0099	TECH_cost_maint	1	0.7	1.1

Table A6 Tilt-Rotor Variable Ranges

Variable	Baseline	Min	Max	Variable	Baseline	Min	Max
alt_eng	6000	4000	6000	Wing_CD	0.013	0.0091	0.0143
temp_eng	95	59	103	TECH_drag	1	0.7	1.1
alt_cruise_out	24000	0	24000	TECH_eng	1	0.7	1.1
alt_cruise_in				TECH_exh	1	0.7	1.1
dist_cruise_out	175.1	157.59	227.63	TECH_plumb	0.984	0.6888	1.0824
dist_cruise_in				TECH_tank	0.803	0.5621	0.8833
dist_dash_out	54	48.6	70.2	TECH_body	0.759	0.5313	0.8349
dist_dash_in				ECH_LG	1.151	0.8057	1.2661
time_loiter	30	27	39	TECH_gb	0.6	0.42	0.66
Wpay_dgw	4020	4000	6600	TECH_blade	0.8	0.56	0.88
Wpay_eng				TECH_hub	1.05	0.735	1.155
Wpay_mission				TECH_rfold	0.85	0.595	0.935
CWs	0.1367	0.12303	0.17771	TECH_fit	0.95	0.665	1.045
fstall		0.7	1.1	TECH_prim	0.81	0.567	0.891
Ki_hover	1.1346	1.05	1.25	TECH_RWfc_b	0.459	0.3213	0.5049
fSDGW	1	0.7	1.2	TECH_RWfc_mb	0.702	0.4914	0.7722
fWMTO	1.25	0.875	1.5	TECH_RWhyd	1.078	0.7546	1.1858
CD	0.0041	0.00287	0.00451	Pacc_0	60	42	187
Swet	1156	809.2	1271.6	SPOC_tech	200	120	260
DoQ_fit	1.2	0.84	1.32	sfc0C_tech	0.3577	0.25039	0.39347
kDrag_hub				TECH_cost_af	1	0.7	1.1
CD_pylon	0.00904	0.006328	0.009944	TECH_cost_maint	1	0.7	1.1

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